Preserving Patient Privacy in Dynamic Treatment Regimes

Dylan Spicker Erica E.M. Moodie Susan M. Shortreed

Department of Epidemiology, Biostatistics and Occupational Health
McGill University

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Precision Medicine

Treat the patient, not the disease.

Individualized Treatment Rules: Mathematical Statement

We want to estimate a decision function,

$$d\colon \mathcal{H} \longrightarrow \mathcal{A} = \{0, 1\},$$

where $H \in \mathcal{H}$ is the patient history and $A \in \mathcal{A}$ is the treatment decision.

We call this function a individualized treatment rule (ITR).

ITR Estimation as Classification

An ITR, d, has value

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Optimal ITRs maximize the value.

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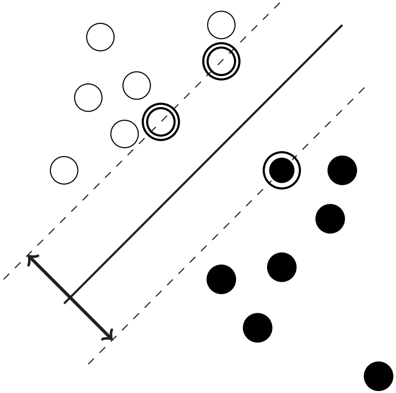
$$E[R|A = 1] + E[R|A = -1] - V(d) = E\left[\frac{R}{P(A|H)} I(A \neq d(H))\right].$$

Outcome-Weighted Learning (OWL)

Outcome-Weighted Learning (OWL) estimates optimal ITRs by minimizing a regularized, empirical version of this error.

Support Vector Machines (SVM)



SVMs use hyperplanes to solve classification problems.

The resulting classifier exists as

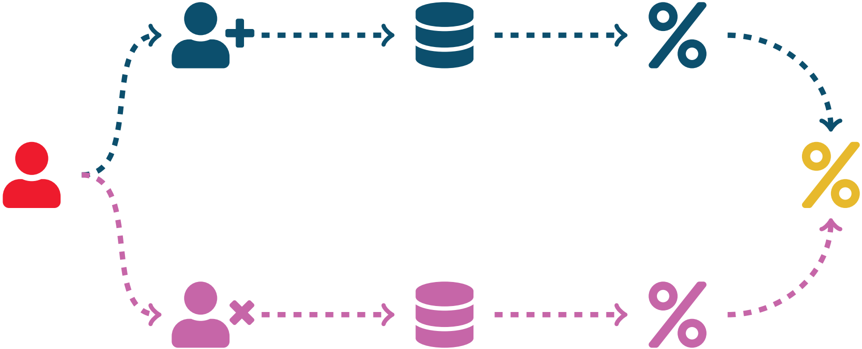
$$f(H) = \sum_{i \in \mathcal{SV}} \alpha_i A_i K(H_i, H).$$

Privacy Implications of SVMs

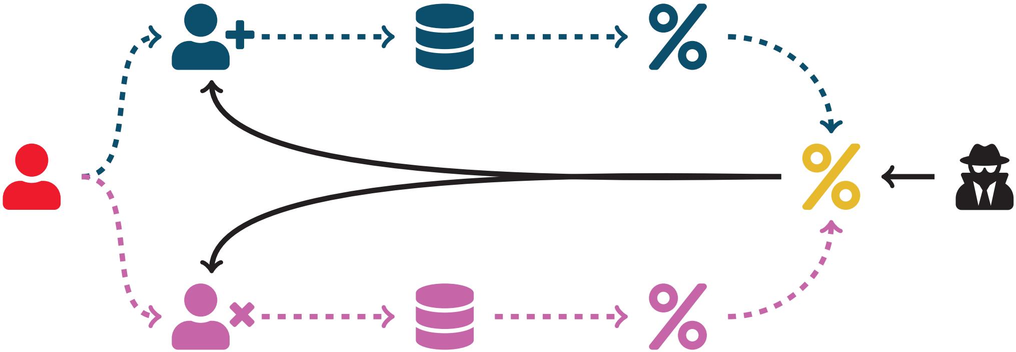
Generally, the resulting decision function requires the **direct release** of the support vectors.

$$f(H) = \sum_{i \in \mathcal{SV}} \alpha_i A_i \exp\left(-\sigma^2 \| H_i - H \|\right)$$

Differential Privacy



Differential Privacy



Differential Privacy: Mathematical Statement

We say that an estimator, $\mathcal{M}$, is ϵ-differentially private if for **all** neighbouring datasets, $\mathbb{X}$ and $\mathbb{X}^\dagger$, we have:

$$\frac{P(\mathcal{M}(\mathbb{X}) \in \mathcal{Y})}{P(\mathcal{M}(\mathbb{X}^\dagger) \in \mathcal{Y})} \leq e^{\epsilon}.$$

Private Outcome-Weighted Learning (PrOWL)

We propose a differentially private implementation of OWL, called PrOWL.

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2. Compute the standard OWL estimator.
3. Perturb the vector with Laplace distributed errors.

PrOWL Guarantees

Quantifiable privacy-accuracy tradeoffs.

Agreement on meaningful treatments w.h.p.

Agreement on optimal value w.h.p.

Summary

Privacy should be a major concern within precision medicine and beyond.

Differential privacy provides one framework for addressing these concerns, with promising results thus far.

Thank You!

www.dylanspicker.com | dylan.spicker@mcgill.ca